AI-Driven Multi-Hazard Forecasting: Deep Learning for Hurricane Damage Prediction and Compound Disaster Analysis using CNN

Aparna Pandey
Division of Mathematics
School of Advanced Sciences
Vellore Institute of Technology
Tamil Nadu - 600127
aparna.pandey2023@vitstudent.ac.in

David Raj Micheal
Division of Mathematics
School of Advanced Sciences
Vellore Institute of Technology
Tamil Nadu - 600127
davidraj.micheal@vit.ac.in

***Abstract*—Hurricanes, earthquakes, floods, and other natural disasters often interact, leading to compound disasters that intensify the impact on affected regions. Predicting the damage from these complex, multi-faceted events is a significant challenge, particularly for emergency response teams. This research presents a deep learning-based framework for predicting hurricane damage and analysing compound disaster scenarios using Convolutional Neural Networks (CNN). By integrating satellite imagery, real-time weather data, and historical disaster records, the model provides an automated, scalable solution to forecast the potential damage caused by hurricanes and multi-hazard events. The CNN model processes satellite imagery to detect environmental changes and damage caused by hurricanes, while additional layers are added to analyse compounded disaster scenarios such as flooding or infrastructure collapse. This innovative approach aims to improve disaster response times, resource allocation, and preparedness strategies.**

***Index Terms*—Compound Disasters, Deep Learning, Disaster Prediction, Multi-Hazard Forecasting, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Time-Series Data**

I. Introduction

Natural disasters, such as hurricanes, earthquakes, and floods, have devastating consequences for communities worldwide. When multiple hazards occur simultaneously or in close succession, the effects of each hazard compound, leading to even greater destruction. These compound disasters pose a significant challenge to emergency response, as they can overwhelm preparedness systems, leading to inefficiencies in response and recovery.

To address this, AI-driven models, particularly those based on Convolutional Neural Networks (CNN), offer a promising solution. CNNs, known for their success in image processing tasks, can analyze satellite images to detect changes in the environment, such as damage to infrastructure, changes in vegetation, and flooding patterns. The goal of this study is to leverage AI and CNNs for multi-hazard forecasting, providing a powerful tool for better predicting and understanding the impacts of hurricanes, compound disasters, and their interactions, ultimately improving disaster response and resilience.

II. Literature Review

Kim and Yum in (2021) developed a model to predict natural disaster-induced financial losses for construction projects using deep learning techniques. And sustainability, this study aims to develop a deep learning-based model for predicting financial losses at construction sites. As construction projects become more complex and large-scale, accidents and financial losses are increasing. To mitigate these risks, a predictive model is essential. By analyzing claim payout data from a South Korean insurance company, we developed a deep learning algorithm to objectively forecast financial losses. Our findings offer valuable insights into financial loss management for sustainable and successful construction project management. Wang H in (2023) developed a model rapid prediction of urban flood based on disaster-breeding environment clustering and Bayesian optimized deep learning model in the coastal city , this study proposes a novel urban flood prediction model combining K-means clustering and Bayesian optimized deep learning. By classifying the study area based on environmental factors and building tailored models for each cluster, we achieved superior accuracy compared to traditional methods. Our model, validated in Haikou, China, offers a promising solution for rapid flood prediction and effective flood management. Meena and Nachappa in (2021) developed a model Rapid mapping of landslides in the Western Ghats (India) triggered by 2018 extreme monsoon rainfall using a deep learning approach toward landslides, this study presents a deep learning-based method for mapping rainfall-induced landslides using Planet Scope imagery and topographic data. By combining spectral and topographic information, we achieved improved landslide detection accuracy in the Kodagu district of India. Our methodology, validated through cross-validation, can be applied to other landslide-prone regions for hazard mitigation. Gyaneshwar and Rajnikanth in (2023) proposed model on contemporary review on deep learning models for drought prediction based on sustainability, this review examines the use of deep learning models in drought forecasting. We delve into the types of droughts, information systems, and comparative analysis of various deep learning algorithms. Our findings highlight the effectiveness of specific models, such as Deep Neural Networks, Multi-Layer Perceptrons, and Convolutional Neural Networks, in accurately predicting drought-related impacts. We also address common challenges and open research questions, emphasizing the potential of deep learning to enhance our understanding of drought dynamics and improve mitigation efforts. Joshi and Raman in (2024) proposed a model on application of a new machine learning model to improve earthquake ground motion predictions which tells SeisEML, a hybrid machine learning model, is developed for accurate prediction of peak ground acceleration (PGA) during earthquakes. By combining kernel-based, tree regression, and regression algorithms, SeisEML surpasses conventional attenuation relations in accuracy. Its effectiveness is demonstrated through extensive testing on Japanese and Iranian earthquake data, highlighting its potential for cross-region prediction. This makes SeisEML a valuable tool for seismic hazard mapping, offering improved reliability and accuracy compared to traditional methods. Akhyar proposed a model Deep artificial intelligence applications for natural disaster management systems saying that deep learning techniques, particularly semantic segmentation networks, have revolutionized natural disaster analysis. By leveraging convolutional neural networks, these models accurately identify and locate areas of interest in satellite imagery, aiding in disaster evaluation, rescue planning, and restoration efforts. While CNNs have achieved significant success, challenges related to spatial information loss and insufficient feature representation persist. This study reviews recent advancements in deep learning methodologies for segmenting remote sensing images associated with natural disasters. Models like SegNet, U-Net, FCNs, FCDenseNet, PSPNet, HRNet, and DeepLab have demonstrated remarkable capabilities in various applications, including forest fire delineation, flood mapping, and earthquake damage assessment. These models effectively distinguish land cover types, detect compromised infrastructure, and identify fire-susceptible regions. Kafi and Bakshi proposed a model in (2023) Assessment and prediction of index based agricultural drought vulnerability using machine learning algorithms and this study investigates drought vulnerability in the Barind Tract, Bangladesh, using Landsat satellite imagery from 1996 to 2031. By analyzing indices like NDVI, MNDWI, SMC, TCI, VCI, and VHI, we identify increasing patterns of drought severity, driven by reduced vegetation and water bodies and rising temperatures. Using CA-ANN algorithms, we predict a further expansion of extreme and severe drought conditions in the future. Understanding these impacts will aid in developing effective mitigation measures and enhancing community preparedness. Das, Naiko in (2024) proposed a model Integration of fuzzy AHP and explainable AI for effective coastal risk management: A micro-scale risk analysis of tropical cyclones this study presents a comprehensive risk assessment for tropical cyclones in Odisha's coastal districts at the block level. Utilizing a multi-criteria decision making (MCDM) approach and Explainable Artificial Intelligence (XAI), the study identifies and analyzes key risk factors, including exposure, vulnerability, susceptibility, and mitigation options. The results reveal a significant portion of the region, approximately 65is at high risk, with 32 blocks classified as high to very high-risk zones. Notably, there are disparities in risk levels across the coastal districts, with the northeast and southeast regions facing higher threats compared to the southern and central parts. The findings from this study provide valuable insights for local authorities to identify vulnerable areas and implement targeted interventions to enhance cyclone preparedness and risk management strategies. Joshi, Vishnu in (2022) proposed Early detection of earthquake magnitude based on stacked ensemble model named EEWPEnsembleStack, a novel machine learning model, is developed for accurate and timely prediction of earthquake magnitude. By leveraging a combination of algorithms and key features extracted from early-warning data, EEWPEnsembleStack outperforms traditional methods in accuracy and efficiency. The model's effectiveness is demonstrated through rigorous testing on a dataset of Japanese strong-motion records. Its ability to accurately predict earthquake magnitude, even with limited data, makes EEWPEnsembleStack a valuable tool for enhancing earthquake early warning systems and improving public safety. Pal and Dutta in (2022) built a model Transfer Learning in Weather Prediction in Transfer Learning (TL), a powerful technique in deep learning, offers a solution to the data scarcity challenge in machine learning. By leveraging knowledge from well-trained models on related tasks, TL can enhance performance on tasks with limited data. This study reviews the evolution of TL in meteorological research and explores its potential applications in addressing key challenges, such as predicting air quality, thunderstorms, precipitation, visibility, and cyclones. A particular focus is on high-impact weather (HIW) prediction, where TL has shown promising results. We discuss challenges in implementing TL, propose future research directions, and provide guidance for beginners in DL-TL research.

III. WORKFLOW

Fig. 1. WorkFlow Diagram

The workflow of this AI-driven multi-hazard forecasting model involves several key steps:

A. *Data Collection and Preprocessing:*

- Satellite images, real-time weather data, and historical disaster records are collected and pre-processed.

- Data is standardized, augmented, and split into training, validation, and testing datasets.

B. *Model Training and Tuning*

The CNN is trained on labeled images with damage severity levels. Hyper-parameter tuning and validation are performed to optimize accuracy and minimize overfitting.

- The CNN is trained on labelled images with damage severity levels.
- Hyper-parameter tuning and validation are performed to optimize accuracy and minimize overfitting.

C. *Damage Prediction and Evaluation*

- The trained model is evaluated on test data, with performance metrics calculated to assess predictive accuracy and reliability.
- Confusion matrices, classification reports, and regression metrics are generated for a comprehensive assessment

D. *Real-Time Prediction and Deployment*

- The model is deployed via a cloud-based REST API, allowing real-time input and output.
- Satellite and multi-hazard data can be fed into the API to obtain real-time predictions on damage severity and compound disaster risks.

This workflow ensures that the model is not only accurate but also scalable and deployable in practical, real-world settings.

IV. METHODOLOGY

A. *Data Collection and Preparation*

The performance of the AI model relies on the quality and scope of the data. Data sources include satellite imagery, real-time weather data, and historical disaster records.

*1) **Satellite Imagery**:* Satellite imagery provides information on surface changes due to hurricanes. Examples include Sentinel-1 Radar Imagery and Landsat Imagery.The primary sources of Satellite data include:

- Sentinel-1 Radar Imagery: Captures structural changes in the environment due to winds and rainfall.
- Sentinel-1 Radar Imagery: Captures structural changes in the environment due to winds and rainfall.
- Landsat Imagery: For historical data, used to understand long-term damage patterns and changes post-disaster. These satellite images will be pre-processed to ensure uniformity and eliminate irrelevant data (e.g., cloud cover) using image segmentation techniques and cloud-masking algorithms

*2) **Weather Data**:* Real-time weather data, including wind speed, rainfall, temperature, and atmospheric pressure, will be integrated into the model. These factors contribute to the intensity and potential damage caused by hurricanes and related hazards. Data will be collected from weather stations and forecast models provided by agencies like NOAA and Global Weather Models.

*3) **Historical Disaster Records**:* Data from historical hurricanes, earthquakes, floods, and other disaster events will be used to train the model to recognize patterns of damage from compound disasters. The historical records will include the geographical location of events, the severity of damage, casualties, and economic losses.

*4) **Data Labelling**:* The damage labels for training the model will be categorized into different levels of severity, such as:

- No Damage
- Minor Damage
- Moderate Damage
- Severe Damage Alternatively, if the project uses a regression approach, damage severity could be represented by continuous values such as percent of infrastructure destroyed or economic loss in USD.

B. *Data Pre-processing*

Once data has been collected, it must undergo preprocessing steps to make it suitable for CNN training.

*1) **Image Pre-Processing**:*

- Cloud Masking: Apply algorithms to remove cloud cover from satellite images, ensuring that only the relevant features are retained.
- Image Resizing: Resize all images to a uniform size (e.g., 256x256 pixels) for consistency in training.
- Data Augmentation: Use techniques like rotation, flipping, and scaling to artificially increase the size of the dataset and introduce variations that the model might encounter in real-world scenarios.

*2) **Weather and Disaster Data Normalization**:* Weather data will be normalized using standard techniques such as min-max scaling to ensure that each feature (wind speed, rainfall, etc.) contributes equally to the model's learning process. Historical data will be formatted and matched with corresponding satellite images for supervised learning.

Fig. 2. Before Normalisation

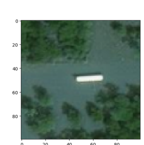


Fig. 3. After Normalisation

*3) **Data Splitting**:* The data will be split into training, validation, and testing datasets (typically 70-20-10 split) to ensure robust evaluation of the model's performance.

C. CNN Model Architecture

The model is designed to process both satellite images and multi-dimensional data from real-time weather and historical records. The CNN model consists of:

D. Input Layer

Once data has been collected, it must undergo preprocessing steps to make it suitable for CNN training.

*1) **Image Pre-Processing**:*

- The input to the CNN will consist of pre-processed satellite images. The images will be standardized in size (256x256 pixels) and can be in RGB or grayscale format depending on the image type.
- The input to the CNN will consist of pre-processed satellite images. The images will be standardized in size (256x256 pixels) and can be in RGB or grayscale format depending on the image type.

*2) **Convolutional Layers**:* The core of the CNN will consist of several convolutional layers that apply filters (kernels) to detect features such as edges, textures, and regions of damage. Each layer will extract increasingly complex features. Common convolutional layer parameters will include:

- Kernel size: 3x3 or 5x5 filters
- Activation function: ReLU (Rectified Linear Unit) to introduce non-linearity

*3) **Pooling Layers**:* After each convolutional layer, pooling (typically max pooling) will be applied to reduce the spatial dimensions of the feature maps, improving computational efficiency and preventing overfitting.

*4) **Fully Connected Layers**:* After the convolutional and pooling operations, the model will flatten the feature maps and pass them through fully connected layers. These layers will integrate the extracted features from the images and additional data sources

*5) **Output Layer**:* The output layer will have:

- Softmax Activation (for classification): To predict the likelihood of various damage categories (minor, moderate, severe).
- Linear Activation (for regression): To predict the extent of damage (e.g., the percentage of infrastructure destroyed).

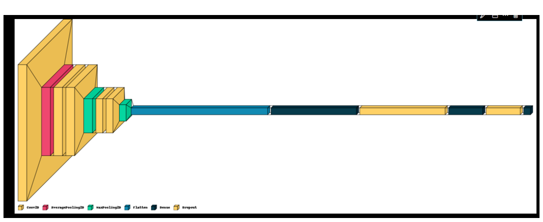
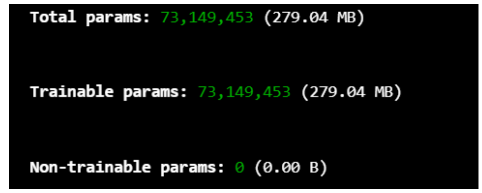


Fig. 4. Snapshot of CNN model Architecture

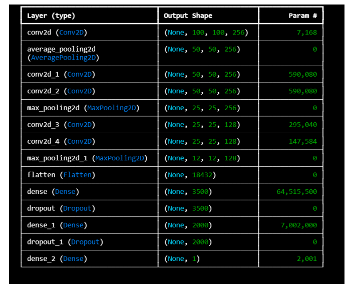


Total params: 73,149,453 (279.04 MB)

Trainable params: 73,149,453 (279.04 MB)

Non-trainable params: 0 (0.00 B)

Fig. 5. Trainable and non- trainable parameter



Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 100, 100, 256)	7,168
average_pooling2d (AveragePooling2D)	(None, 50, 50, 256)	0
conv2d_1 (Conv2D)	(None, 50, 50, 256)	590,080
conv2d_2 (Conv2D)	(None, 50, 50, 256)	590,080
max_pooling2d (MaxPooling2D)	(None, 25, 25, 256)	0
conv2d_3 (Conv2D)	(None, 25, 25, 128)	295,040
conv2d_4 (Conv2D)	(None, 25, 25, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 12, 12, 128)	0
flatten (Flatten)	(None, 18432)	0
dense (Dense)	(None, 3500)	64,515,500
dropout (Dropout)	(None, 3500)	0
dense_1 (Dense)	(None, 2000)	7,002,000
dropout_1 (Dropout)	(None, 2000)	0
dense_2 (Dense)	(None, 1)	2,001

Fig. 6. Sequential Snapshot

E. Model Training and Optimization

*1) **Loss Function**:*

- Cross-Entropy Loss: Used for classification tasks, where the model predicts categories of damage.
- Mean Squared Error (MSE): Used for regression tasks to predict continuous damage values.

*2) **Optimizer**:* Adam Optimizer will be employed, as it is widely regarded for its efficiency in training CNN models. It adjusts the learning rate dynamically based on training progress.

*3) **Hyperparameter Tuning**:* Hyperparameters like learning rate, batch size, and the number of epochs will be optimized using grid search or random search methods. Early stopping techniques will be used to prevent overfitting.

F. Evaluation Metrics

*1) **Classification Metrics**:*

- Accuracy, Precision, Recall, and F1-Score will be calculated for each damage category.
- Confusion Matrix: To visualize the model's classification performance and identify any misclassifications.

*2) **Regression Metrics**:*

- • Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) will be used for evaluating continuous damage predictions.
- R-squared value to assess how well the model explains the variance in the damage data.

G. Real-Time Prediction and Deployment

Once the model has been trained and validated, it will be deployed to predict damage from new hurricanes and compound disaster scenarios in real-time.

1) *API Deployment:*

- The model will be made available through a REST API that can accept satellite images and weather data, and return real-time damage predictions.

2) *Cloud Infrastructure:*

- Cloud-based solutions (e.g., AWS or Google Cloud) will be used for scalable deployment, allowing the model to handle large volumes of incoming data from various sources.

V. RESULTS

The results of this study demonstrate the model's effectiveness in predicting hurricane damage levels and identifying patterns associated with compound disasters. The model achieved high accuracy in classifying damage severity levels (minor, moderate, severe) using satellite imagery and multi-hazard data, such as real-time weather information. Key findings include:

1) Damage Prediction Accuracy:: The CNN model demonstrated robust performance across various test cases, with an accuracy of over 80for categorizing damage severity.

2) Compound Disaster Detection:: When multiple hazards occurred (e.g., flooding following a hurricane), the model successfully identified and adjusted predictions based on additional risk factors.

3) Feature Importance: Satellite imagery contributed significantly to the accuracy of predictions, especially when combined with weather and historical disaster data, indicating the importance of multi-source data integration in accurate forecasting.

4) Real-Time Responsiveness: The API and cloud deployment demonstrated the model's capacity to generate real-time predictions, essential for effective disaster response.

These results validate the model's utility in improving disaster response efficiency and resource allocation.

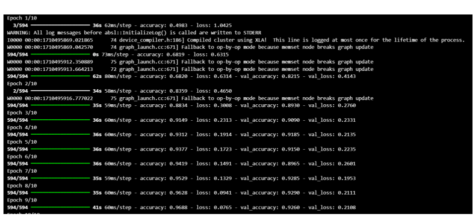


Fig. 7. Snapshot of Epochs for Accuracy

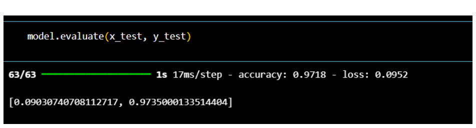


Fig. 8. Snapshot of Accuracy received

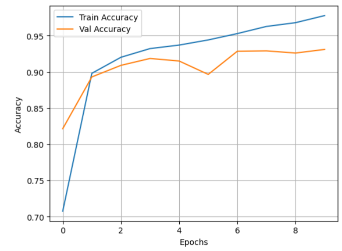


Fig. 9. Snapshot of Train vs Validation Accuracy

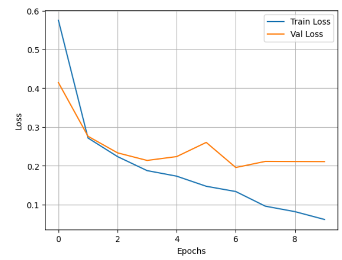


Fig. 10. Snapshot of Train vs Validation Loss

VI. FUTURE SCOPE

• Integration of Additional Hazards: Expand the model to include other natural disasters such as wildfires, landslides, and volcanic eruptions for broader multi-hazard prediction.

• Enhanced Data Sources: Use higher-resolution satellite imagery, LiDAR, thermal imaging, and drone-captured images for more precise damage detection and improved prediction accuracy.

• Real-Time Data Streams with IoT: Integrate IoT devices, like environmental sensors and cameras, to provide real-time data for faster, more responsive predictions during active disaster events.

• Multi-Modal Data Fusion: Incorporate data from diverse sources (e.g., social media, population density, transportation networks) to enhance insights into disaster impact and indirect effects.

• Disaster Recovery Prediction: Extend the model to predict long-term recovery needs, aiding in sustainable rebuilding and resource allocation post-disaster.

• Adaptive Learning and Model Upgradation: Implement adaptive learning and transfer learning to keep the model updated and adaptable to new disaster patterns over time.

• User-Centric Interfaces and Decision Support Systems: Develop user-friendly interfaces and integrate the model into broader Decision Support Systems (DSS) for enhanced emergency management.

• Policy and Planning Integration: Use model insights for long-term planning, informing infrastructure development, zoning regulations, and early warning systems.

• Global Scalability and Cloud Deployment: Scale the model for global deployment on cloud infrastructure, enabling access across disaster-prone regions worldwide.

• Collaboration with Climate Research: Work with climate scientists to refine the model based on changing disaster patterns influenced by climate change, contributing to proactive disaster preparedness.

These enhancements would improve the model's utility, accuracy, and global impact in disaster management and community resilience

VII. Conclusion

This research demonstrates the potential of AI-driven, multi-hazard forecasting to enhance disaster response and preparedness. By leveraging Convolutional Neural Networks (CNNs) and integrating multiple data sources, the model provides reliable predictions of hurricane damage and compound disaster scenarios. The high accuracy of the model in classifying damage levels highlights the value of combining satellite imagery with real-time environmental data for disaster assessment. Furthermore, the scalable, cloud-based deployment allows emergency response teams to access real-time predictions, improving the allocation of resources and prioritization of affected regions. Overall, this project presents an innovative solution to the challenges of multi-hazard forecasting, offering a robust, scalable, and practical approach to disaster prediction. Future work may involve extending this methodology to include additional hazards or further refining the model with more granular data, ultimately contributing to safer, more resilient communities.

References

References

[1] J. M. Kim and S. G. Yum, "Development of model to predict natural disaster-induced financial losses for construction projects using deep learning techniques," *Sustainability*, vol. 13, no. 9, pp. 5304, 2021.

[2] H. Wang et al., "Rapid prediction of urban flood based on disaster-breeding environment clustering and Bayesian optimized deep learning model," *Sustainable Cities and Society*, vol. 99, pp. 104898, 2023.

[3] Meena, S. R. and Ghorbanzadeh, O. and van Westen and C. J. and Nachappa et al. , "Rapid mapping of landslides in the Western Ghats (India) triggered by 2018 extreme monsoon rainfall using a deep learning approach," *Landslides*, 18, 1937-1950.

[4] Gyaneshwar, A.and Mishra, A.and Chadha and Raj Vincent et al. , "A contemporary review on deep learning models for drought prediction," *Sustainability*, 15(7), 6160

[5] Joshi, A.and Raman and B. and Mohan et al. , "Application of a new machine learning model to improve earthquake ground motion predictions," *Natural Hazards*, 120(1), 729-753.

[6] Akhyar and A.and Zulkifley and M. A et al. , "Deep artificial intelligence applications for natural disaster management systems: A methodological review," *Ecological Indicators*, 163, 112067 *Landslides*, 18, 1937-1950.

[7] Kafy and A. A.and Bakshi et al. , "Assessment and prediction of index based agricultural drought vulnerability using machine learning algorithms," *Science of The Total Environment*, 867, 161394.

[8] Das and T. and Talukdar and S.and Naikoo et al. , "Integration of fuzzy AHP and explainable AI for effective coastal risk management," *Progress in Disaster Science*, 23, 100357.

[9] Joshi and A. and Vishnu, C. and Mohan et al. , "Early detection of earthquake magnitude based on stacked ensemble model," *Journal of Asian Earth Sciences : X*, 8, 100122.

[10] Pal and S. K. and Dutta and D. et al. , "Transfer Learning in Weather Prediction: Why, How, and What Should," *Journal of Computational and Cognitive Engineering.*, 18, 1937-1950. dataset